Evaluating Perceived Workload, Usability and Usefulness of Artificial Intelligence Systems in Low-Resource Settings: Semi-Automated Classification and Detection of Community Acquired Pneumonia

Malaizyo Muzumala[1[0009−0003−4338−7268]], Ernest Obbie Zulu[2[0009−0005−3260−7717]], Peter Chibuta[2[0009−0002−0129−6790]], Mayumbo Nyirenda[1[0000−0002−9615−3487]], and Lighton Phiri[3[0000−0003−3582−9866]]

[1] Department of Computer Science University of Zambia, Lusaka, Zambia
{malaizyo.muzumala,mayumbo.nyirenda}@cs.unza.zm

[2] Department of Radiology, University Teaching Hospitals, Lusaka, Zambia
{obbiernest,chibutapeter75}@gmail.com

[3] Department of Library and Information Science, University of Zambia, Lusaka, Zambia
lighton.phiri@unza.zm

Abstract. The use of Artificial Intelligence (AI) techniques in radiological workflows is increasingly becoming mainstream. However, the uptake of AI techniques is still low in low-resource settings in places such as the Global South. This paper presents a study conducted in a setting with low AI uptake, to determine the impact of AI on Radiologists' workload when interpreting medical images. Two (2) AI models—a classification model and detection model indicating potential areas of interest—were implemented to facilitate the semi-automated interpretation of medical images for Pneumonia. In addition, a Web-based DICOM Viewer was implemented to interface the AI models. To determine the appropriate model configuration, two (2) experts—a Radiologist and Radiology Resident—participated in a focus group discussion aimed at determining how the AI models could facilitate interpretation processes. A comparative controlled experiment was subsequently conducted with 12 Radiology Residents at a large University Teaching Hospital, to assess the impact of AI on the workload and its perceived usefulness. NASA Task Load Index (TLX) and Technology Acceptance Model (TAM) 2 questionnaires were employed to measure the workload and usefulness. The results indicate that the perceived workload is significantly less when using the AI solution, with an overall NASA-TLX score of 1.86. Furthermore, the perceived usefulness of the AI solution is demonstrated through the positive responses for all the eight TAM 2 constructs. This study experimentally demonstrates the potential of utilising AI for the semi-automated interpretation of medical images in low-resource settings.

Keywords: Artificial Intelligence · Classification · Detection · DICOM · Medical Images.

1 Introduction

The lack of availability of adequate radiological resources in health facilities in low-resource settings is well documented [12], with factors such as shortfall of Radiologists and unavailability of required infrastructure cited as the major factors.

The rapid advances in the field of Artificial Intelligence (AI) provides opportunities to address the many challenges associated with radiological workflows. However, the adoption of such AI solutions has been slow in resource-poor health institutions in regions such as the Global South.

This paper presents work conducted in a Global South country, Zambia, to explore how AI could be deployed and integrated within medical imaging workflows and, additionally, assess its effectiveness.

In order to execute the study, pneumonia was used as a case pathology. Pneumonia is reported to have been one of the top 10 leading causes of both morbidity and, additionally, one of the top five leading causes of mortality in Zambia in 2021; Pneumonia was the second highest cause of death in 2021, contributing to 11.4% of the total deaths [19]. The increase in Pneumonia cases and reported shortage of Radiologists in Zambia presents a challenge with effective diagnoses, especially in regards to medical image interpretation. Artificial Intelligence (AI) has been identified as a potentially viable approach to effectively and efficiently interpreting medical images. These tools will be used to assist clinicians in the radiographic diagnosis of Community Acquired Pneumonia (CAP), helping them to select patients eligible for antibiotic therapy.

While the use of AI in health facilities in Zambia is still in its infancy, our previous work has, in part, identified opportunities for leveraging AI [28]. In addition, we have demonstrated the feasibility of deploying Enterprise Medical Imaging technologies such as Picture Archiving and Communication Systems (PACS), which provide the base infrastructure required for the deployment of AI-based solutions.

This work was aimed at demonstrating how Artificial Intelligence (AI) can be leveraged to support the semi-automated diagnosis of pneumonia in low-resource settings characterised by experts with little experience working with AI centric solutions.

The main contributions of this work are as follows:

- Results from Radiologists and Medical Doctors' perceptions on the use of AI for the semi-automated interpretation of medical images
- Experimental results on the usefulness of using classification, localisation and detection models

The remainder of this paper is organised as follows: Section 2 outlines state-of-the-art literature related to this work; Section 3 describes the methodological approach used to execute studies associated with this work; Section 4 provides the presentation of findings and their interpretation and, finally, Section 5 outlines concluding remarks and future work.

2 Related Work

2.1 Pneumonia in the Global South

Pneumonia is an acute respiratory infection responsible for a significant global disease burden as measured by the loss in Disability Adjusted Life Years (DALYs) [6] The impact of pneumonia is much more severe in developing countries due to low rates of childhood immunisation, poor nutrition, overcrowding, smoking and increased at-risk populations with comorbid immunosuppressive conditions such as HIV infection. In Zambia—for instance—Pneumonia remains among the top causes of morbidity and mortality (1). Chest radiography is recognised as the standard reference for the diagnosis of CAP [3] as there are no reliable clinical features, individually or in combination, to establish the diagnosis [11]. However, developing countries are faced with a critical shortage of Radiologists for effective interpretation of the chest radiographs. Management of suspected CAP has typically involved empirical treatment with broad spectrum antibiotics, with recent observations provoking concerns for contribution towards the rise in antimicrobial-resistant strains [4]. Therefore, tools to support clinicians in the radiographic diagnosis of CAP would assist in the careful selection of patients eligible for antibiotic therapy.

2.2 Automated Interpretation of Medical Image

Existing literature highlights three image recognition techniques—classification, detection and localisation—and segmentation as the broad category of approaches that are employed when applying AI within medical image interpretation workflows. Fournier and Chassagnon provide a comprehensive description of these approaches, including case scenarios when such approaches are applied [7]

A number of AI models have been proposed to aid in the interpretation of variable radiographs and pathologies, including detection of pneumonia. Chumbita et al. provide a review of how AI can potentially be used to improve the management of pneumonia [5]. Another review by Stokes et al. investigates performance and reporting of AI systems for pneumonia detection [22].

In addition, there are more focused studies that have resulted in the implementation of AI models for detecting pneumonia. For instance, Li et al. propose a deep learning for detecting pneumonia [10]. Other studies include work by Račić et al., who demonstrate how chest x-rays can be processed by AI algorithms to support decision making [17].

Existing work aimed at evaluating the effects of AI solutions on radiological workflows suggests different aspects of the perceptions practitioners have towards AI tools [8, 27]

3 Methodology

A mixed-method approach was employed when conducting this study, with the CRoss Industry Standard Process for Data Mining (CRISP-DM) [26] methodology used to guide the overall research process.

Ethical clearance was granted by The University of Zambia Biomedical Research Ethics Committee (Reference Number: 2731-2022) and The National Health Research Authority (Reference Number: NHRA000024/10/05/2022), to conduct this study. In addition, formal permission was granted from The University Teaching Hospital (UTHs).

3.1 Pneumonia Classification and Detection Models

The goal of this study was to comprehensively evaluate the perceived use of AI models for the semi-automated interpretation of medical images. Two Pneumonia AI models—a binary classification model and a detection model—were implemented, in part, to determine the appropriate approach for integrating AI solutions into medical imaging workflows.

The classification model was built using transfer learning from VGG16 [21] on the Paul Mooney chest x-ray dataset [13]. The full implementation is public [2]. The detection model was trained on the RSNA dataset, full implementation and data is public [1].

The two models were deployed by implementing a Web-based interface which, aside from rendering responses from the model, provided comprehensive DICOM Data Element metadata. The interaction between the Web-based interface and the models was facilitated by a Web service, implemented to accept requests from the Web interface and produce responses from the models.

The AI models were implemented to use a DICOM file as input. The binary classification model was implemented to signal if a given input DICOM file was associated with Pneumonia.

The Python programming language was used to implement the models, primarily using the Kaggle platform for training and community support. The publicly available "RSNA Pneumonia Detection Challenge" [16] and "Chest X-Ray Pneumonia" [13] datasets were used to train the detection model. The Web service was implemented using Python Flask [15], while the Web interface was implemented using Next.js [25]]. Standard classification [18] and detection [14] performance metrics were employed to assess the effectiveness of the two models as outlined in Section 4.

3.2 Effectiveness of Semi-Automated Interpretation

The adoption of AI in radiological workflows at UTH is still in its infancy and as such, to evaluate the potential of using AI for the semi-automated interpretation of medical images, experiments were conducted to assess the effect of AI on the turnaround time and workload. In addition, the perceived usefulness of AI solutions was assessed.

Semi-Automated Medical Image Interpretation Approaches In order to determine how the classification and detection models would be integrated within the medical imaging workflow, a virtual focus group discussion was held with two Key Experts: a Radiologist (Radiologist 1) with 5 years experience and a Radiology Resident (Radiology Resident 1) with 1 year experience. The two Key Experts were sampled using convenience sampling from UTHs.

The discussion with the Key Experts was focused on determining if the AI intervention should be deployed with either one of the two models or a combination of the two models. In addition, the Key Experts were requested to provide feedback on potential changes that could be made to the Web-interface.

Evaluating Perceived Workload and Usefulness A controlled experiment was conducted in order to experimentally evaluate the AI toolkit through the measurement of perceived workload, usefulness and usability.

To evaluate the perceived workload and usefulness, a comparative analysis was conducted by comparing the AI solution (AI Intervention) with the conventional way of interpreting medical images (Baseline), generally involving the use of DICOM Viewers.

Evaluation of the perceived workload and usefulness associated with the AI intervention was conducted with participants—Radiology Residents and General Practitioners—sampled from UTHs. UTHs has a shortage of Radiologists, as outlined in our prior work [28] and as a result, Radiology Residents and General Practitioners are compelled to interpret medical images. The participants were sampled using convenience sampling.

Measurement Instruments. The NASA Task Load Index (NASA-TLX) instrument [9][23] was used to measure the participants' perceived workload. The NASA-TLX instrument measures subjective workload scores using a weighted rating of six subscales—Mental Demand, Physical Demand, Temporal Demand, Performance, Effort and Frustration.

The perceived usefulness and usability of the AI toolkit was measured using the Technology Acceptance Model (TAM 2) instrument [24]. TAM 2 facilitates the measurement of users' perceived usefulness and perceived ease of use of a technology, along with additional social influence and cognitive instrumental processes, to predict their intention to use the technology.

*Task Design and Experiment Procedure.*Study participants were required to interpret a Chest X-ray positive for Pneumonia using the two approaches—the implemented AI solution, a combination of the classification and detection models—AI Intervention—and the conventional way of interpreting medical images—Baseline. Counterbalancing of interpretation approaches was employed by changing the order in which the two approaches were used.

Participants were briefed about the study and subsequently required to sign an informed consent form. Participants subsequently performed the experiment tasks, completing the NASA-TLX immediately after performing the predefined task using each of the two approaches. After completion of the task using the two approaches, the participants were required to complete the TAM 2 questionnaire, to provide their perceived subjective views of using the AI toolkit.

4 Results and Discussion

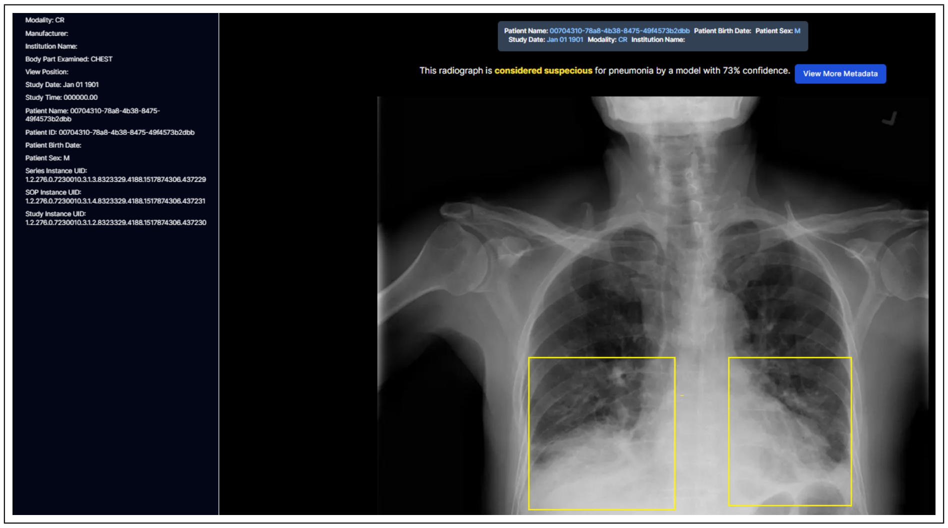

Fig. 1. A screenshot of the localiser interface.

4.1 Pneumonia Classification and Detection

The classification model had an accuracy of 72% and the detection model had an Intersection over union of 12% and precision of 15%. In addition, the recall for the detection model was 79%, with a 30% overlap threshold in area to count it as a hit. The basis of the threshold was the observed tendency of the model to draw the regions larger than the annotated drawings.

The classification accuracy, was lower than some existing studies [20] future training will work with these and better workflows. However, the low Intersection over union is primarily attributed to the model's tendency to give false positives. Drawing the boxes larger than the annotating radiologists. A proposed mitigation was using the two (2) models together such that the bounding model would only act when the classification model returns a positive result.

4.2 Efficiency and Effectiveness of Semi-Automated Interpretation

The focus group discussions held with the two experts indicate that the ideal configuration would have to combine information from both the classification model (text indicating the positivity of the semi-automated interpretation) and detection model (bounding boxes indicating the potential areas of interest). [Radiologist 1] indicated that they preferred the combined method, further suggesting changes to technical terms used in the Web interface. The message from the classifier was changed from "This case is suspected Positive for pneumonia by a model with 73% accuracy" with the "positive" in red to "This radiograph is considered suspicious for pneumonia by a model with 73% confidence" with considered suspicious bounding box in yellow. In addition, [Radiology Resident 1] also preferred the combined approach, and suggested images be sent to the model and processes as soon as they're onboarded without needing to click a button. Figure 1 shows a screenshot of the interface combining results from the classification and detection models.

A total of 12 participants—one (1) Radiologist, six (6) Radiology Residents and five (5) Other Practitioners—participated in the comparative study to assess perceived workload and usefulness associated with the AI solution. While the participants were generally aware of AI based on the discussions around the experiment, none of them stated they had experience applying AI solutions when interpreting medical images.

Perceived Workload The NASA-TLX average workload (mean weights for each practitioner in each category) for the AI Intervention and the Baseline were 1.86 and 2.22 (lower numbers are better), respectively, indicating that the perceived workload for the AI Intervention is lower than the Baseline. Figure 2 shows the mean weights for each of the six (6) NASA-TLX subscales, grouped by interpretation approach.

The results further indicate that the perceived workload was noticeably lower, when using the AI Intervention, for the "Mental", "Physical", and "Effort". This is arguably the expected effect of an AI solution since automation results in users performing significantly less tasks. While the workload was lower when using the Baseline for "Temporal", "Performance" and "Frustration", the variation was not significant. More importantly, however, the perceived less workload for "Temporal" is arguably because participants were already familiar with interpreting medical images associated with Pneumonia while using DICOM Viewers. The same argument can be made for the lower score for "Performance", since users are generally more effective when using tools they are familiar with. Finally, the lower score for the "Frustration" subscale is likely due to the fact that participants were interacting with the AI Intervention for the first time.

Ultimately, the results of the perceived workload evaluation, especially suggest a need to expose Radiologists and General Practitioners at UTHs to AI tools. This view is shared by RAD-AID, who propose a three-pronged approach for AI adoption in resource-constrained environments [12]

Perceived Usefulness The results from the TAM 2 questionnaires were analysed using the eight (8) TAM 2 constructs using the standard approach for analysing TAM 2 responses . The results of the analysis are shown in Figure 3.

Most of the participants had positive responses for all the eight TAM 2 construction, with participants overwhelmingly agreeing with "Intention to Use", "Results Demonstrability" and "Voluntariness". Some participants, in particular, negatively rated the "Job Relevance" and "Output Quality".

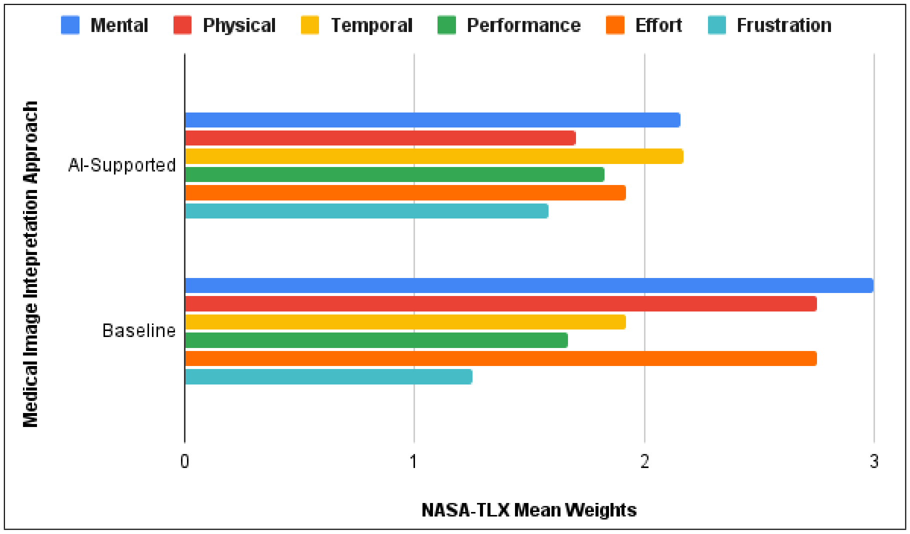

Fig. 2. NASA-TLX Mean Weights comparison between AI intervention and baseline.

The negative response for "Output Quality" can arguably be because that single participant disagreed with the result of the model. That was the sole participant that rated the section negatively. The negative responses linked to "Job Relevance" can mostly be attributed to Radiologists that have extensive experience interpreting medical images linked to Pathologies like Pneumonia and it can be argued that they would likely agree with the relevance of more challenging modalities to interpret..

Participants' Comments Participants were required to provide optional comments regarding the AI intervention. The comments—outlined below—ranged from recommendations on how to use such AI solutions and, additionally, suggestions on how to improve the solution.

"Needs to be in the right hands, users should be able to interpret (medical back)" [sic] [Participant 4]

"I would only recommend radiology residents and radiologists to use such tools. As other doctors may have challenges"[sic] [Participant 4]

"Strong recommended working with specialised pneumonias" [Participant 7]

"There should be a way of inputting the medical details with the xray" [sic] [Participant 9]

"wouldn't recommend for complex imaging. Like CTs" [sic] [Participant 11]

The comments support the results from the TAM 2 usefulness evaluation and in particular, results associated with the "Subjective Norm", "Job Relevance" and "Perceived Ease of Use" TAM 2 constructs.

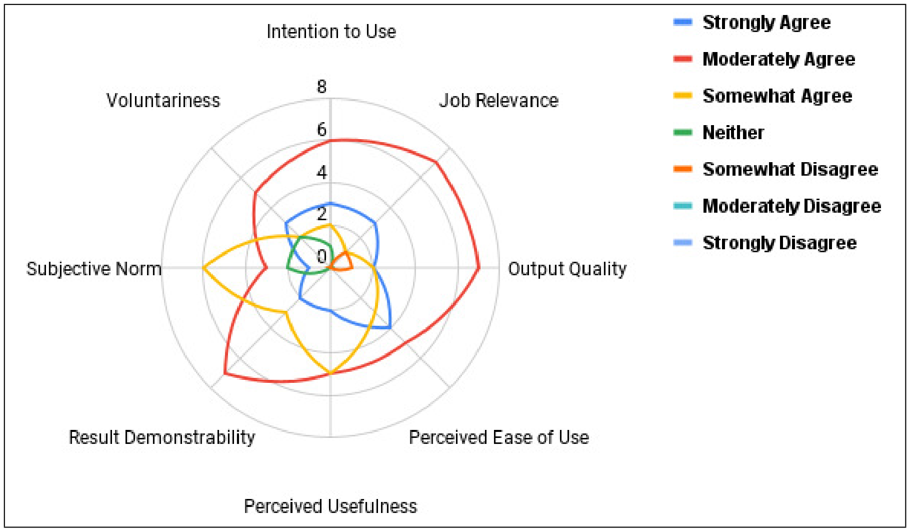

Fig. 3. Radar Chart illustrating the summary of the usability evaluation results.

5 Conclusion

This paper detailed a study conducted in a low-resource setting of a Global South country in order to demonstrate the perceived effectiveness of utilising AI solutions to address challenges characteristic of radiological workflows. Pneumonia was used as the case pathology in order to assess the effect of the AI solution on the workload and potential usefulness of the solution.

The results from this study arguably provide vital insights into perceptions of Radiologists and General Practitioners on the impact of AI solutions when applied to radiological workflows.

Acknowledgments. This study was conducted as part of a much larger "Enterprise Medical Imaging in Zambia" project. The project is funded through generous grants from Google Research, Data Science Africa and The University of Zambia. We are very appreciative of this funding.

References

1. EMI: Detection model, MRCNN and COCO. https://www.kaggle.com/code/malaizyogmuzumala/emi-detection-model-mrcnn-and-coco?scriptVersionId=165890883 (Mar 2024), accessed: 2024-7-25
2. EMI simple pneumonia based binary classifier. https://www.kaggle.com/code/malaizyogmuzumala/emi-simple-pneumonia-based-binary-classifier (Mar 2024), accessed: 2024-7-25

3. Boersma, W.G., Daniels, J.M.A., Löwenberg, A., Boeve, W.J., van de Jagt, E.J.: Reliability of radiographic findings and the relation to etiologic agents in community-acquired pneumonia. Respiratory Medicine **100**(5), 926–932 (May 2006). https://doi.org/https://doi.org/10.1016/j.rmed.2005.06.018
4. Boyles, T.H., Brink, A., Calligaro, G.L., Cohen, C., Dheda, K., Maartens, G., Richards, G.A., van Zyl Smit, R., Smith, C., Wasserman, S., Whitelaw, A.C., Feldman, C., South African Thoracic Society, Federation of Infectious Diseases Societies of Southern Africa: South african guideline for the management of community-acquired pneumonia in adults. Journal of Thoracic Disease **9**(6), 1469–1502 (Jun 2017). https://doi.org/https://doi.org/10.21037/jtd.2017.05.31
5. Chumbita, M., Cillóniz, C., Puerta-Alcalde, P., Moreno-García, E., Sanjuan, G., Garcia-Pouton, N., Soriano, A., Torres, A., Garcia-Vidal, C.: Can artificial intelligence improve the management of pneumonia. Journal of Clinical Medicine **9**(1) (Jan 2020). https://doi.org/https://doi.org/10.3390/jcm9010248
6. Ferkol, T., Schraufnagel, D.: The global burden of respiratory disease. Annals of the American Thoracic Society **11**(3) (Mar 2014). https://doi.org/https://doi.org/10.1513/annalsats.201311-405ps
7. Fournier, L., Chassagnon, G.: Artificial Intelligence and Machine Learning, pp. 213–225. Springer US, New York, NY (2021). https://doi.org/10.1007/978-1-0716-1756-4_14
8. Gaube, S., Suresh, H., Raue, M., Lermer, E., Koch, T.K., Hudecek, M.F.C., Ackery, A.D., Grover, S.C., Coughlin, J.F., Frey, D., Kitamura, F.C., Ghassemi, M., Colak, E.: Non-task expert physicians benefit from correct explainable AI advice when reviewing x-rays. Scientific Reports **13**(1), 1383 (Jan 2023). https://doi.org/https://doi.org/10.1038/s41598-023-28633-w
9. Hart, S.G., Staveland, L.E.: Development of NASA-TLX (task load index): Results of empirical and theoretical research. In: Hancock, P.A., Meshkati, N. (eds.) Human Mental Workload, Advances in Psychology, vol. 52, pp. 139–183. North-Holland (Jan 1988). https://doi.org/https://doi.org/10.1016/S0166-4115(08)62386-9
10. Li, L., Qin, L., Xu, Z., Yin, Y., Wang, X., Kong, B., Bai, J., Lu, Y., Fang, Z., Song, Q., Cao, K., Liu, D., Wang, G., Xu, Q., Fang, X., Zhang, S., Xia, J., Xia, J.: Using artificial intelligence to detect COVID-19 and community-acquired pneumonia based on pulmonary CT: Evaluation of the diagnostic accuracy. Radiology (Mar 2020). https://doi.org/https://doi.org/10.1148/radiol.2020200905
11. Metlay, J.P., Kapoor, W.N., Fine, M.J.: Does This Patient Have Community-Acquired Pneumonia?: Diagnosing Pneumonia by History and Physical Examination. JAMA **278**(17), 1440–1445 (11 1997). https://doi.org/10.1001/jama.1997.03550170070035
12. Mollura, D.J., Culp, M.P., Pollack, E., Battino, G., Scheel, J.R., Mango, V.L., Elahi, A., Schweitzer, A., Dako, F.: Artificial intelligence in low- and Middle-Income countries: Innovating global health radiology. Radiology **297**(3), 513–520 (Oct 2020). https://doi.org/https://doi.org/10.1148/radiol.2020201434
13. Mooney, P.: Chest x-ray images (pneumonia) (Mar 2018), https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia
14. Padilla, R., Netto, S.L., da Silva, E.A.B.: A survey on performance metrics for object-detection algorithms. In: 2020 International Conference on Systems, Signals and Image Processing (IWSSIP). IEEE (Jul 2020). https://doi.org/https://doi.org/10.1109/IWSSIP48289.2020.9145130
15. Pallets: Welcome to flask - flask documentation (3.0.x). https://flask.palletsprojects.com/en/3.0.x (2010), accessed: 2024-3-7

16. Pan, I., Cadrin-Chênevert, A., Cheng, P.M.: Tackling the radiological society of north america pneumonia detection challenge. American Journal of Roentgenology **213**(3), 568–574 (2019). https://doi.org/10.2214/AJR.19.21512, https://doi.org/10.2214/AJR.19.21512, pMID: 31120793
17. Racic, L., Popovic, T., Cakic, S., Sandi, S.: Pneumonia detection using deep learning based on convolutional neural network. In: 2021 25th International Conference on Information Technology (IT). IEEE (Feb 2021). https://doi.org/https://doi.org/10.1109/IT51528.2021.9390137
18. Reich, Y., Barai, S.V.: Evaluating machine learning models for engineering problems. Artificial Intelligence in Engineering **13**(3), 257–272 (Jul 1999). https://doi.org/https://doi.org/10.1016/S0954-1810(98)00021-1
19. Republic of Zambia Ministry of Health: Annual health statistical report 2017 - 2021: Tracking performance of the NHSP 2017 - 2021. Tech. rep., Republic of Zambia Ministry of Health (Oct 2022), https://www.moh.gov.zm/?wpfb_dl=179
20. Reshan, M.S.A., Gill, K.S., Anand, V., Gupta, S., Alshahrani, H., Sulaiman, A., Shaikh, A.: Detection of pneumonia from chest x-ray images utilizing MobileNet model. Healthcare (Basel) **11**(11) (May 2023). https://doi.org/https://doi.org/10.3390/healthcare11111561
21. Simonyan, K., Zisserman, A.: Very deep convolutional networks for large-scale image recognition (2015), https://arxiv.org/abs/1409.1556
22. Stokes, K., Castaldo, R., Federici, C., Pagliara, S., Maccaro, A., Cappuccio, F., Fico, G., Salvatore, M., Franzese, M., Pecchia, L.: The use of artificial intelligence systems in diagnosis of pneumonia via signs and symptoms: A systematic review. Biomedical Signal Processing and Control **72**, 103325 (2022). https://doi.org/https://doi.org/10.1016/j.bspc.2021.103325
23. The NASA TLX Tool: Task Load Index: TLX @ NASA ames - home. https://humansystems.arc.nasa.gov/groups/tlx/, accessed: 2024-3-7
24. Venkatesh, V., Davis, F.D.: A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science **46**(2), 186–204 (Feb 2000). https://doi.org/https://doi.org/10.1287/mnsc.46.2.186.11926
25. Vercel, Inc.: Next.js by vercel - the react framework. https://nextjs.org, accessed: 2024-3-7
26. Wirth, R., Hipp, J.: CRISP-DM: Towards a standard process model for data mining. In: Proceedings of the Fourth International Conference on the Practical Application of Knowledge Discovery and Data Mining. pp. 29–39 (2000), http://cs.unibo.it/ danilo.montesi/CBD/Beatriz/10.1.1.198.5133.pdf
27. Xie, Y., Chen, M., Kao, D., Gao, G., Chen, X.a.: CheXplain: Enabling physicians to explore and understand Data-Driven, AI-Enabled medical imaging analysis. In: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. pp. 1–13. CHI '20, Association for Computing Machinery, New York, NY, USA (Apr 2020). https://doi.org/https://doi.org/10.1145/3313831.3376807
28. Zulu, E.O., Phiri, L.: Enterprise medical imaging in the global south: Challenges and opportunities. In: 2022 IST-Africa Conference (IST-Africa). pp. 1–9. IEEE (May 2022). https://doi.org/https://doi.org/10.23919/IST-Africa56635.2022.9845508